

Datenvorbereitung_Regression

Socken- (Schuh-) Daten in geeignetes Format bringen

... um trainierte Netzwerke mit geeigneten Daten zu "füttern". Ersetzt die Schritte die in Matlab bereits für die Trainingsdaten ausgeführt wurden, unter Vernachlässigung der Bindungsdaten und derer Synchronisation.

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.axes as ax
import tensorflow as tf
import seaborn as sns
sns.set_style("whitegrid")
current_palette = sns.color_palette('colorblind')
#np.set_printoptions(threshold=np.inf) #um alle array einträge anzeigen zu lassen
```

Sockendaten...

In [2]:

```
sock_data1 = pd.read_csv('Regression_Daten/socketest1.txt', delimiter='\t', header=0)
sock_data2 = pd.read_csv('Regression_Daten/socketest2.txt', delimiter='\t', header=0)
sock_data3 = pd.read_csv('Regression_Daten/socketest3.txt', delimiter='\t', header=0)
#sock_data
#sock_data.shape
```

In [3]:

```
sock_data1.shape, sock_data2.shape, sock_data3.shape
```

Out [3]:

```
((899, 25), (662, 25), (8626, 25))
```

Berücksichtige nur Daten zwischen erstem und letztem Trigger:

In [4]:

```
#Finde Triggerpunkte
x = sock_data1.Trigger
trig=[]
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x == y]
trig=get_indexes(1,x)
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
sock_data1=sock_data1.drop(sock_data1.index[range(max(trig)+1,len(sock_data1.index))])
sock_data1=sock_data1.drop(sock_data1.index[range(0,min(trig))])

x = sock_data2.Trigger
trig=[]
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x == y]
trig=get_indexes(1,x)
```

```

sock_data2=sock_data2.drop(sock_data2.index[range(max(trig)+1,len(sock_data2.index))])
sock_data2=sock_data2.drop(sock_data2.index[range(0,min(trig))])

x = sock_data3.Trigger
trig=[]
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x == y]
trig=get_indexes(1,x)

sock_data3=sock_data3.drop(sock_data3.index[range(max(trig)+1,len(sock_data3.index))])
sock_data3=sock_data3.drop(sock_data3.index[range(0,min(trig))])

```

In [5]:

```
#sock_data1.shape, sock_data2.shape, sock_data3.shape, 8626*2
```

Upsampling der Daten

In [6]:

```

sock_data1=sock_data1.rename(columns={"Milisec": "ms"})
sock_data1.ms = np.linspace(start=0,stop=(len(sock_data1)*100-100),num=len(sock_data1))#(sock_data1)
#Mache Indizes zu "TimedeltaIndizes" --> Voraussetzung zum einfachen Resampeling
sock_data1.index = pd.TimedeltaIndex(sock_data1.ms, unit='ms')
sock_data1 = sock_data1.drop(columns="Time") #Time ein tf-object das nicht mehr benötigt wird
sock_data1 = sock_data1.resample('50L').asfreq() #upsampling: '50L' entspricht 50ms
sock_data1 = sock_data1.interpolate(method='linear')
#sock_data1 = sock_data1[1:]

```

In [7]:

```

sock_data2=sock_data2.rename(columns={"Milisec": "ms"})
sock_data2.ms = np.linspace(start=0,stop=(len(sock_data2)*100-100),num=len(sock_data2))#(sock_data2)
#Mache Indizes zu "TimedeltaIndizes" --> Voraussetzung zum einfachen Resampeling
sock_data2.index = pd.TimedeltaIndex(sock_data2.ms, unit='ms')
sock_data2 = sock_data2.drop(columns="Time") #Time ein tf-object das nicht mehr benötigt wird
sock_data2 = sock_data2.resample('50L').asfreq() #upsampling: '50L' entspricht 50ms
sock_data2 = sock_data2.interpolate(method='linear')
sock_data2 = sock_data2[1:]

```

In [8]:

```

sock_data3=sock_data3.rename(columns={"Milisec": "ms"})
sock_data3.ms = np.linspace(start=0,stop=(len(sock_data3)*100-100),num=len(sock_data3))#(sock_data3)
#Mache Indizes zu "TimedeltaIndizes" --> Voraussetzung zum einfachen Resampeling
sock_data3.index = pd.TimedeltaIndex(sock_data3.ms, unit='ms')
sock_data3 = sock_data3.drop(columns="Time") #Time ein tf-object das nicht mehr benötigt wird
sock_data3 = sock_data3.resample('50L').asfreq() #upsampling: '50L' entspricht 50ms
sock_data3 = sock_data3.interpolate(method='linear')
sock_data3 = sock_data3[1:]

```

In [9]:

```
sock_data1.shape, sock_data2.shape, sock_data3.shape,
```

Out [9]:

```
((1191, 24), (1018, 24), (16898, 24))
```

Daten für das Training der NNs vereinen

In [10]:

```
frames = [sock_data1, sock_data2, sock_data3]
sock_data = pd.concat(frames, axis=0)
#print(sock_data)
```

Setze den Millisekunden(ms)-Startwert des Dataframes (df) auf Null

In [11]:

```
sock_data=sock_data.rename(columns={"Milisec": "ms"})
sock_data.ms = np.linspace(start=0,stop=(len(sock_data)*50-50),num=len(sock_data))#(sock_data.ms-sock_data.ms).mean()
#Mache Indizes zu "TimedeltaIndizes" --> Voraussetzung zum einfachen Resampling
sock_data.index = pd.TimedeltaIndex(sock_data.ms, unit='ms')
```

In [12]:

```
#plt.plot(sock_data.index)
```

In [13]:

```
sock_data = sock_data.drop(['ms', 'M1A6', 'M2A6', 'Trigger'], axis=1) #Unnötige Spalten fallen lassen
```

In [14]:

```
#sock_data
```

Aufteilen der Daten in Trainings und in Testdaten:

| | | |
|---------|---------|-----|
| x_train | y_train | 60% |
| x_val | y_val | 16% |
| x_test | y_test | 24% |

In [15]:

```
train = 0.60
val = 0.16
test = 0.24
idx_val = round(train*len(sock_data))
#idx_val = int(idx_val/batchsize)*batchsize
idx_test = round((train+val)*len(sock_data))
x_train_val = sock_data[:idx_test]
x_test0 = sock_data[idx_test:]
```

Normierung der Daten

In [16]:

```
mean = x_train_val.mean(axis=0)
x_train_val -= mean
std = x_train_val.std(axis=0)
x_train_val /= std

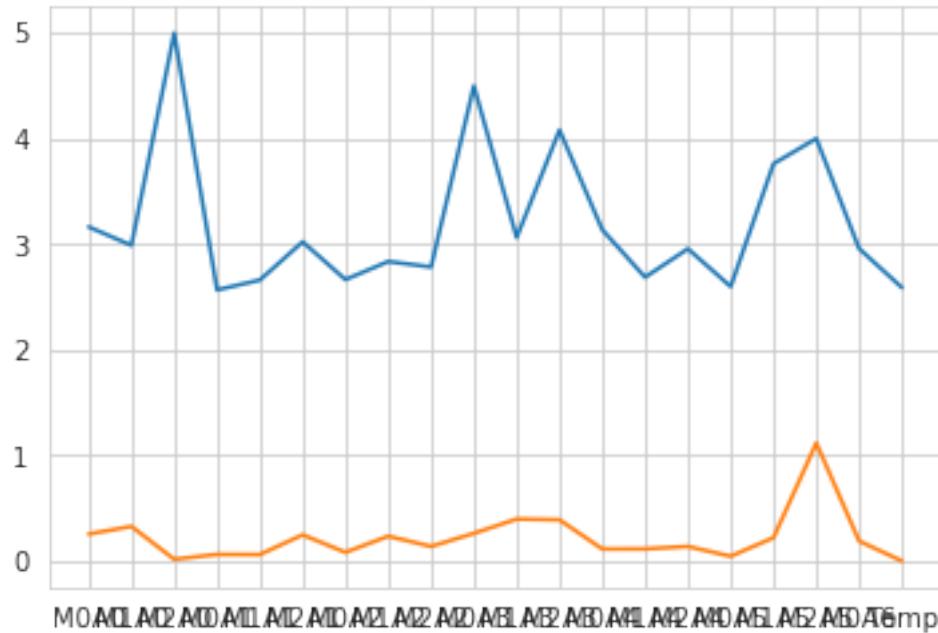
x_test0 -= mean #muss mit gleichen mean/std-Werten geschehen
x_test0 /= std #--"
```

In [17]:

```
#np.save('NormData_mean',mean)
#np.save('NormData_std',std)
```

In [18]:

```
plt.figure()
plt.plot(mean)
plt.plot(std)
plt.show()
```



Teilen der Trainings- und Validierungsdaten

In [19]:

```
x_train0 = x_train_val[:idx_val]
x_val0 = x_train_val[idx_val:]
```

In [20]:

```
x_train0.shape, x_val0.shape, x_test0.shape
```

Out [20]:

```
((11464, 20), (3057, 20), (4586, 20))
```

Reshaping...

... zu Format (samples, timesteps, features)

In [21]:

```
samples = None
timesteps = 22 #Auf 22 sek festgelegt (22*0.05s = 1.1s) ; ungleich 20 um von features.shape unterscheiden
features = len(x_train0.columns) #Anzahl der Sensoren
step = 1 #Versatz zum nächsten Sample; ungerade damit Interpolierte und ursprüngliche Werte abwechseln
```

```
batchsize = 128
```

In [22]:

```
a = int((len(x_train0))-timesteps)/step)
b = int((len(x_val0))-timesteps)/step)
c = int((len(x_test0))-timesteps)/step)
```

In [23]:

```
temp = np.ndarray((1,timesteps,features))
temp.fill(0)
x_train = np.ndarray((1,timesteps,features))
x_train.fill(0)

for i in range(a):
    for j in range(timesteps):
        for k in range(features):
            temp[0,j,k] = x_train0.iloc[(j+i*step),k]
    x_train = np.concatenate((x_train,temp), axis=0)
x_train = x_train[1:]
```

In [24]:

```
temp = np.ndarray((1,timesteps,features))
temp.fill(0)
x_val = np.ndarray((1,timesteps,features))
x_val.fill(0)

for i in range(b):
    for j in range(timesteps):
        for k in range(features):
            temp[0,j,k] = x_val0.iloc[(j+i*step),k]
    x_val = np.concatenate((x_val,temp), axis=0)
x_val = x_val[1:]
```

In [25]:

```
temp = np.ndarray((1,timesteps,features))
temp.fill(0)
x_test = np.ndarray((1,timesteps,features))
x_test.fill(0)

for i in range(c):
    for j in range(timesteps):
        for k in range(features):
            temp[0,j,k] = x_test0.iloc[(j+i*step),k]
    x_test = np.concatenate((x_test,temp), axis=0)
x_test = x_test[1:]
```

In [26]:

```
x_train = x_train[:int(x_train.shape[0]/batchsize)*batchsize]
```

In [27]:

```
x_val = x_val[:int(x_val.shape[0]/batchsize)*batchsize]
```

In [28]:

```
x_test = x_test[:int(x_test.shape[0]/batchsize)*batchsize]
```

In [29]:

```
x_train.shape, x_val.shape, x_test.shape
```

Out [29]:

```
((11392, 22, 20), (2944, 22, 20), (4480, 22, 20))
```

Bindungsdaten

In [30]:

```
import scipy.io
from keras.utils import np_utils
```

Using TensorFlow backend.

In [31]:

```
#importiere gelabelte Kurvenfahrtendaten
mat1 = scipy.io.loadmat('Regression_Daten/y_Test1.mat')
mat2 = scipy.io.loadmat('Regression_Daten/y_Test2.mat')
mat3 = scipy.io.loadmat('Regression_Daten/y_Test3.mat')
y_mat1=mat1['y_Test1']
y_mat2=mat2['y_Test2']
y_mat3=mat3['y_Test3']
#yKurven.shape
```

betrachte nur Daten zwischen erstem und letztem Trigger

In [32]:

```
x=[]
trig=[]
x = y_mat1[:,3]
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x <= y]
trig=get_indexes(4.5,x)
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
y_mat1=y_mat1[min(trig):max(trig),:]

x = y_mat2[:,3]
trig=[]
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x <= y]
trig=get_indexes(4.5,x)
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
y_mat2=y_mat2[min(trig):max(trig),:]

x = y_mat3[:,3]
trig=[]
get_indexes = lambda x, xs: [i for (y, i) in zip(xs, range(len(xs))) if x <= y]
trig=get_indexes(4.5,x)
#Lösche Zeilen vor erstem und nach letztem Triggerpunkt
```

```
y_mat3=y_mat3[min(trig):max(trig),:]
```

In [33]:

```
y_mat = np.concatenate((y_mat1, y_mat2, y_mat3),axis=0)
```

In [34]:

```
y_mat1.shape, y_mat2.shape, y_mat3.shape, sock_data1.shape, sock_data2.shape, sock_data3.shape,
```

Out [34]:

```
((1191, 4), (1018, 4), (16898, 4), (1191, 24), (1018, 24), (16898, 24))
```

In [35]:

```
# Kontroll-Plot ob Triggerpunkte von Socken und Bindungsdaten übereinstimmen
```

```
fig, (ax1,ax2) = plt.subplots(1,2, figsize=(13, 5), dpi=150, facecolor='w', edgecolor='k', sharey=True)
fig.suptitle('Synchronisationskontrolle der Trainingsdaten von Bindung und Socke')

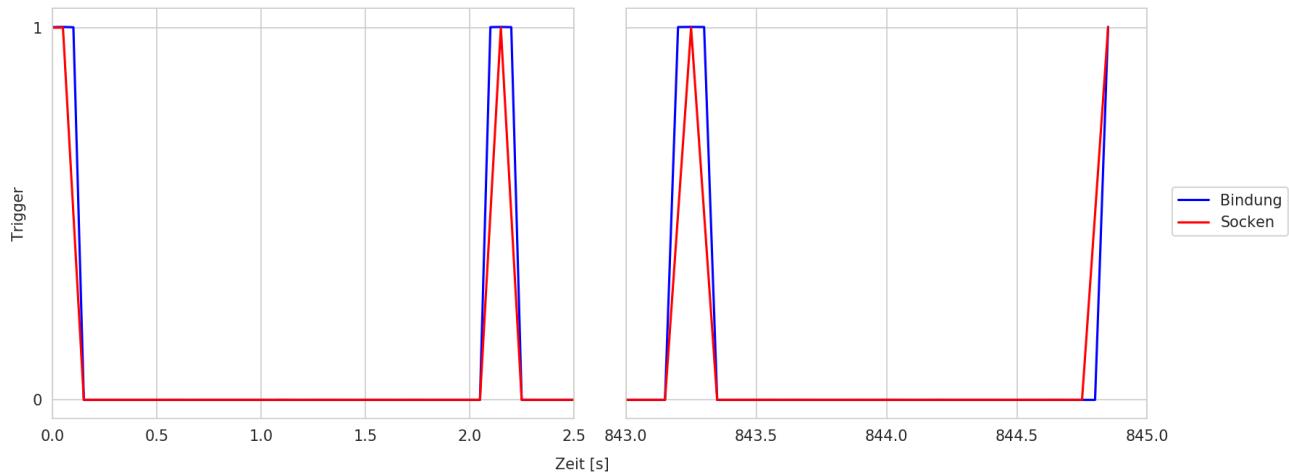
ax1.plot(np.linspace(start=0,stop=len(y_mat3)-1,num=len(y_mat3))*0.05,y_mat3[:,3]/5,'b')
ax1.plot(np.linspace(start=0,stop=len(y_mat3)-1,num=len(y_mat3))*0.05,sock_data3.Trigger,'r')
ax1.set_xlim(0*0.05,50*0.05)
ax1.set(ylabel='Trigger', yticks=[0,1])
#fig.set_xlabel('Row Number of Data')

ax2.plot(np.linspace(start=0,stop=len(y_mat3)-1,num=len(y_mat3))*0.05,y_mat3[:,3]/5, 'b', label='Bindung')
ax2.plot(np.linspace(start=0,stop=len(y_mat3)-1,num=len(y_mat3))*0.05,sock_data3.Trigger, 'r', label='Socken')
ax2.set_xlim(16860*0.05,16900*0.05)
ax2.legend(bbox_to_anchor=(0.8, 0.1, 0.5, 0.5), borderaxespad=1)
fig.subplots_adjust(wspace=0.1)
ax2.set(xticks=[843,843.5,844,844.5,845])
fig.text(0.5, 0.04, 'Zeit [s]', ha='center', va='center')
```

Out [35]:

```
Text(0.5, 0.04, 'Zeit [s]')
```

Synchronisationskontrolle der Trainingsdaten von Bindung und Socke

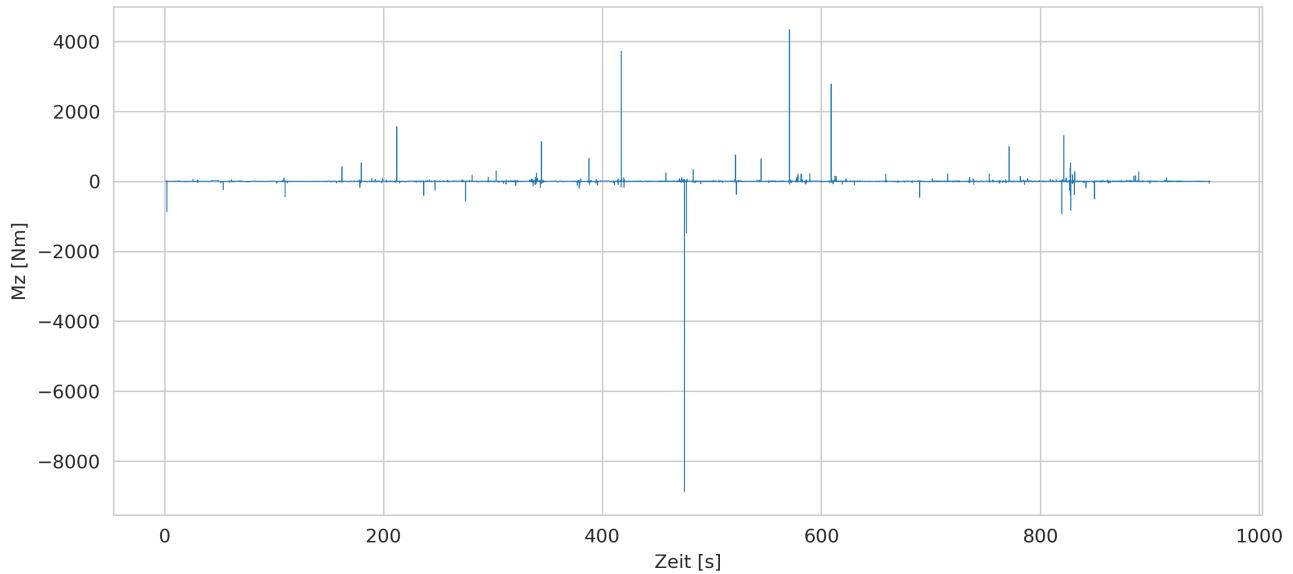


AusreiSSer der Fz-Daten beseitigen

Alle Werte auSSerhalb der 3sigma-Grenze beseitigen und linear interpolieren

In [36]:

```
plt.figure(num=None, figsize=(11, 5), dpi=300, facecolor='w', edgecolor='k'),
plt.plot(np.linspace(1,len(y_mat)*0.05-0.05,len(y_mat)), y_mat[:,2], label='Mz', linewidth=0.5, mew=0)
plt.xlabel('Zeit [s]')
plt.ylabel('Mz [Nm]')
#plt.legend(bbox_to_anchor=(0.65, 0.15, 0.52, 0.4), borderaxespad=0)
#plt.xlim(left=600, right=800)
plt.show()
```



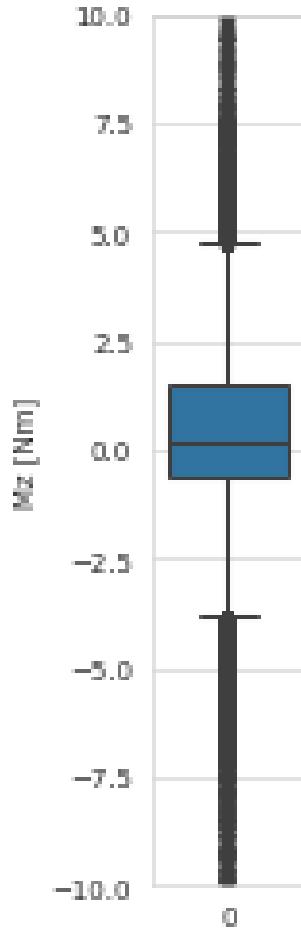
In [37]:

```
print(y_mat.shape)
plt.figure(num=None, figsize=(1, 6), dpi=50, facecolor='w', edgecolor='k'),
plt.ylabel('Mz [Nm]')
#plt.plot(np.linspace(start=0,stop=(len(y_mat3)-1),num=len(y_mat3))*0.05, y_mat3[:,2])
#plt.ylim(bottom=-10, top=10)
plt.ylim(bottom=-10, top=10)
sns.boxplot(data=y_mat[:,2])#, orient='horizontal')
```

(19107, 4)

Out [37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1119d7be0>
```



In [38]:

```
Fz_mean = np.mean(y_mat[:, 2])
Fz_std = np.std(y_mat[:, 2])
Fz_mean, Fz_std
```

Out [38]:

```
(0.5375190907940057, 84.48314548417602)
```

In [39]:

```
Fz_lb = Fz_mean - 3 * Fz_std #untere Grenze (lower bound)
Fz_ub = Fz_mean + 3 * Fz_std #obere Grenze (upper bound)
Fz_lb, Fz_ub
```

Out [39]:

```
(-252.91191736173406, 253.98695554332207)
```

In [40]:

```
#Ersetzen der Ausreier/Fehlenden Werte mit Mean-Werten der Datenreihe
#--> Methode beschrieben in "AN ANALYSIS OF FOUR MISSING DATA TREATMENT METHODS FOR SUPERVISED LEARN
```

```

y_mat_smooth = y_mat
for i in range(len(y_mat_smooth[:,2])):
    if y_mat_smooth[i,2] > Fz_ub:
        y_mat_smooth[i,2]=Fz_mean
    elif y_mat_smooth[i,2] < Fz_lb:
        y_mat_smooth[i,2]=Fz_mean
    else:
        y_mat_smooth[i,2]=y_mat_smooth[i,2]

```

Aufteilen der Daten in Trainings und in Testdaten:

| | | |
|---------|---------|-----|
| x_train | y_train | 60% |
| x_val | y_val | 16% |
| x_test | y_test | 24% |

In [41]:

```
x_train.shape, x_val.shape, x_test.shape
```

Out [41]:

```
((11392, 22, 20), (2944, 22, 20), (4480, 22, 20))
```

In [42]:

```
idx_val, idx_test, a, b, c
```

Out [42]:

```
(11464, 14521, 11442, 3035, 4564)
```

In [43]:

```

y_all_train_val = y_mat_smooth[:idx_test]
y_all_train0 = y_mat_smooth[:idx_val]
y_all_val0 = y_mat_smooth[idx_val:]
y_all_test0 = y_mat_smooth[idx_test:]
#y_all_test0.shape

```

In [44]:

```
#plt.plot(y_mat_smooth[:,2])
```

Y: Bindungsdaten für Trainingsshape (None,Timesteps,1)

verwendet wird dieses Formats bei letzter LSTM-Layer-Einstellung: return_sequence=True

In [45]:

```

#Fz in shape=(None, timesteps, 1)
    #train
temp = np.ndarray((1,timesteps,1))
temp.fill(0)
y_Fz_train1 = np.ndarray((1,timesteps,1))
y_Fz_train1.fill(0)

for i in range(a):
    for j in range(timesteps):
        temp[0,j,0] = y_all_train0[(j+i*step),0] #0 für Fz (1.Spalte)
        y_Fz_train1 = np.concatenate((y_Fz_train1,temp), axis=0)
y_Fz_train1 = y_Fz_train1[1:]

```

```

#val
temp.fill(0)
y_Fz_val1 = np.ndarray((1,timesteps,1))
y_Fz_val1.fill(0)

for i in range(b):
    for j in range(timesteps):
        temp[0,j,0] = y_all_val0[(j+i*step),0] #0 für Fz (1.Spalte)
    y_Fz_val1 = np.concatenate((y_Fz_val1,temp), axis=0)
y_Fz_val1 = y_Fz_val1[1:]

#test
temp.fill(0)
y_Fz_test1 = np.ndarray((1,timesteps,1))
y_Fz_test1.fill(0)

for i in range(c):
    for j in range(timesteps):
        temp[0,j,0] = y_all_test0[(j+i*step),0] #0 für Fz (1.Spalte)
    y_Fz_test1 = np.concatenate((y_Fz_test1,temp), axis=0)
y_Fz_test1 = y_Fz_test1[1:]

y_Fz_train1 = y_Fz_train1[:(:int(y_Fz_train1.shape[0]/batchsize)*batchsize)]
y_Fz_val1 = y_Fz_val1[:(:int(y_Fz_val1.shape[0]/batchsize)*batchsize)]
y_Fz_test1 = y_Fz_test1[:(:int(y_Fz_test1.shape[0]/batchsize)*batchsize)]

```

In [46]:

```

#My in shape=(None, timesteps, 1)
#train
temp = np.ndarray((1,timesteps,1))
temp.fill(0)
y_My_train1 = np.ndarray((1,timesteps,1))
y_My_train1.fill(0)

for i in range(a):
    for j in range(timesteps):
        temp[0,j,0] = y_all_train0[(j+i*step),1] #1 für My (2.Spalte)
    y_My_train1 = np.concatenate((y_My_train1,temp), axis=0)
y_My_train1 = y_My_train1[1:]

#val
temp.fill(0)
y_My_val1 = np.ndarray((1,timesteps,1))
y_My_val1.fill(0)

for i in range(b):
    for j in range(timesteps):
        temp[0,j,0] = y_all_val0[(j+i*step),1] #1 für My (2.Spalte)
    y_My_val1 = np.concatenate((y_My_val1,temp), axis=0)
y_My_val1 = y_My_val1[1:]

```

```

#test
temp.fill(0)
y_My_test1 = np.ndarray((1,timesteps,1))
y_My_test1.fill(0)

for i in range(c):
    for j in range(timesteps):
        temp[0,j,0] = y_all_test0[(j+i*step),1] #1 für My (2.Spalte)
    y_My_test1 = np.concatenate((y_My_test1,temp), axis=0)
y_My_test1 = y_My_test1[1:]

y_My_train1 = y_My_train1[:(:int(y_My_train1.shape[0]/batchsize)*batchsize)]
y_My_val1 = y_My_val1[:(:int(y_My_val1.shape[0]/batchsize)*batchsize)]
y_My_test1 = y_My_test1[:(:int(y_My_test1.shape[0]/batchsize)*batchsize)]

```

In [47]:

```

#My in shape=(None, timesteps, 1)
#train
temp = np.ndarray((1,timesteps,1))
temp.fill(0)
y_Mz_train1 = np.ndarray((1,timesteps,1))
y_Mz_train1.fill(0)

for i in range(a):
    for j in range(timesteps):
        temp[0,j,0] = y_all_train0[(j+i*step),2] #2 für Mz (3.Spalte)
    y_Mz_train1 = np.concatenate((y_Mz_train1,temp), axis=0)
y_Mz_train1 = y_Mz_train1[1:]

#val
temp.fill(0)
y_Mz_val1 = np.ndarray((1,timesteps,1))
y_Mz_val1.fill(0)

for i in range(b):
    for j in range(timesteps):
        temp[0,j,0] = y_all_val0[(j+i*step),2] #2 für Mz (3.Spalte)
    y_Mz_val1 = np.concatenate((y_Mz_val1,temp), axis=0)
y_Mz_val1 = y_Mz_val1[1:]

#test
temp.fill(0)
y_Mz_test1 = np.ndarray((1,timesteps,1))
y_Mz_test1.fill(0)

for i in range(c):
    for j in range(timesteps):
        temp[0,j,0] = y_all_test0[(j+i*step),2] #2 für Mz (3.Spalte)
    y_Mz_test1 = np.concatenate((y_Mz_test1,temp), axis=0)
y_Mz_test1 = y_Mz_test1[1:]

```

```

y_Mz_train1 = y_Mz_train1[:(int(y_Mz_train1.shape[0]/batchsize)*batchsize)]
y_Mz_val1 = y_Mz_val1[:(int(y_Mz_val1.shape[0]/batchsize)*batchsize)]
y_Mz_test1 = y_Mz_test1[:(int(y_Mz_test1.shape[0]/batchsize)*batchsize)]

```

Y: Bindungsdaten für Trainingsshape (None,1)

verwendet diese Formate bei letzter LSTM-Layer-Einstellung: return_sequence=False

In [48]:

```

#Fz in shape=(None,1)
    #train
temp = np.ndarray((1,1))
temp.fill(0)
y_Fz_train2 = np.ndarray((1,1))
y_Fz_train2.fill(0)

for i in range(a):
    temp[0] = y_all_train0[(i*step+timestamps-1),0] #0 für Fz (1.Spalte) +timestamps um ein Sample mit
    y_Fz_train2 = np.concatenate((y_Fz_train2,temp), axis=0)
y_Fz_train2 = y_Fz_train2[1:]

    #val
temp.fill(0)
y_Fz_val2 = np.ndarray((1,1))
y_Fz_val2.fill(0)

for i in range(b):
    temp[0] = y_all_val0[(i*step+timestamps-1),0] #0 für Fz (1.Spalte)
    y_Fz_val2 = np.concatenate((y_Fz_val2,temp), axis=0)
y_Fz_val2 = y_Fz_val2[1:]

    #test
temp.fill(0)
y_Fz_test2 = np.ndarray((1,1))
y_Fz_test2.fill(0)

for i in range(c):
    temp[0] = y_all_test0[(i*step+timestamps-1),0] #0 für Fz (1.Spalte)
    y_Fz_test2 = np.concatenate((y_Fz_test2,temp), axis=0)
y_Fz_test2 = y_Fz_test2[1:]

y_Fz_train2 = y_Fz_train2[:(int(y_Fz_train2.shape[0]/batchsize)*batchsize)]
y_Fz_val2 = y_Fz_val2[:(int(y_Fz_val2.shape[0]/batchsize)*batchsize)]
y_Fz_test2 = y_Fz_test2[:(int(y_Fz_test2.shape[0]/batchsize)*batchsize)]

```

In [49]:

```

#My in shape=(None,1)
    #train
temp = np.ndarray((1,1))
temp.fill(0)
y_My_train2 = np.ndarray((1,1))
y_My_train2.fill(0)

```

```

for i in range(a):
    temp[0] = y_all_train0[(i*step+timestamps-1),1] #1 für My (2.Spalte) +timesteps um ein Sample mit
    y_My_train2 = np.concatenate((y_My_train2,temp), axis=0)
y_My_train2 = y_My_train2[1:]

    #val
temp.fill(0)
y_My_val2 = np.ndarray((1,1))
y_My_val2.fill(0)

for i in range(b):
    temp[0] = y_all_val0[(i*step+timestamps-1),1] #1 für My (2.Spalte)
    y_My_val2 = np.concatenate((y_My_val2,temp), axis=0)
y_My_val2 = y_My_val2[1:]

    #test
temp.fill(0)
y_My_test2 = np.ndarray((1,1))
y_My_test2.fill(0)

for i in range(c):
    temp[0] = y_all_test0[(i*step+timestamps-1),1] #1 für My (2.Spalte)
    y_My_test2 = np.concatenate((y_My_test2,temp), axis=0)
y_My_test2 = y_My_test2[1:]

y_My_train2 = y_My_train2[:(:int(y_My_train2.shape[0]/batchsize)*batchsize)]
y_My_val2 = y_My_val2[:(:int(y_My_val2.shape[0]/batchsize)*batchsize)]
y_My_test2 = y_My_test2[:(:int(y_My_test2.shape[0]/batchsize)*batchsize)]

```

In [50]:

```

#Mz in shape=(None,1)
    #train
temp = np.ndarray((1,1))
temp.fill(0)
y_Mz_train2 = np.ndarray((1,1))
y_Mz_train2.fill(0)

for i in range(a):
    temp[0] = y_all_train0[(i*step+timestamps-1),2] #2 für Mz (3.Spalte) +timesteps um ein Sample mit
    y_Mz_train2 = np.concatenate((y_Mz_train2,temp), axis=0)
y_Mz_train2 = y_Mz_train2[1:]

    #val
temp.fill(0)
y_Mz_val2 = np.ndarray((1,1))
y_Mz_val2.fill(0)

for i in range(b):
    temp[0] = y_all_val0[(i*step+timestamps-1),2] #2 für Mz (3.Spalte)
    y_Mz_val2 = np.concatenate((y_Mz_val2,temp), axis=0)
y_Mz_val2 = y_Mz_val2[1:]

```

```

#test
temp.fill(0)
y_Mz_test2 = np.ndarray((1,1))
y_Mz_test2.fill(0)

for i in range(c):
    temp[0] = y_all_test0[(i*step+timestamps-1),2] #2 für Mz (3.Spalte)
    y_Mz_test2 = np.concatenate((y_Mz_test2,temp), axis=0)
y_Mz_test2 = y_Mz_test2[1:]

y_Mz_train2 = y_Mz_train2[:(:int(y_Mz_train2.shape[0]/batchsize)*batchsize)]
y_Mz_val2 = y_Mz_val2[:(:int(y_Mz_val2.shape[0]/batchsize)*batchsize)]
y_Mz_test2 = y_Mz_test2[:(:int(y_Mz_test2.shape[0]/batchsize)*batchsize)]

```

In [51]:

```
a, b, c
```

Out [51]:

```
(11442, 3035, 4564)
```

In [52]:

```
x_train.shape[0], x_val.shape[0], x_test.shape[0]
```

Out [52]:

```
(11392, 2944, 4480)
```

In [53]:

```
# Kontrolle längre Trainingsdaten
y_Fz_train1.shape[0], y_Fz_train2.shape[0], y_My_train1.shape[0], y_My_train2.shape[0], y_Mz_train1.
```

Out [53]:

```
(11392, 11392, 11392, 11392, 11392)
```

In [54]:

```
# Kontrolle längre Validierungsdaten
y_Fz_val1.shape[0], y_Fz_val2.shape[0], y_My_val1.shape[0], y_My_val2.shape[0], y_Mz_val1.shape[0],
```

Out [54]:

```
(2944, 2944, 2944, 2944, 2944)
```

In [55]:

```
# Kontrolle längre Testdaten
y_Fz_test1.shape[0], y_Fz_test2.shape[0], y_My_test1.shape[0], y_My_test2.shape[0], y_Mz_test1.shape[0]
```

Out [55]:

```
(4480, 4480, 4480, 4480, 4480)
```

Abspeichern der Trainings- Validierungs- und Testdaten der Eingabe x und Ausgabe y

In [56]:

```
"""np.save('Regression_Daten/x_train', x_train)
np.save('Regression_Daten/x_val', x_val)
np.save('Regression_Daten/x_test', x_test)
```

```

np.save('Regression_Daten/y_Fz_train1', y_Fz_train1)
np.save('Regression_Daten/y_Fz_val1', y_Fz_val1)
np.save('Regression_Daten/y_Fz_test1', y_Fz_test1)

np.save('Regression_Daten/y_My_train1', y_My_train1)
np.save('Regression_Daten/y_My_val1', y_My_val1)
np.save('Regression_Daten/y_My_test1', y_My_test1)

np.save('Regression_Daten/y_Mz_train1', y_Mz_train1)
np.save('Regression_Daten/y_Mz_val1', y_Mz_val1)
np.save('Regression_Daten/y_Mz_test1', y_Mz_test1)

np.save('Regression_Daten/y_Fz_train2', y_Fz_train2)
np.save('Regression_Daten/y_Fz_val2', y_Fz_val2)
np.save('Regression_Daten/y_Fz_test2', y_Fz_test2)

np.save('Regression_Daten/y_My_train2', y_My_train2)
np.save('Regression_Daten/y_My_val2', y_My_val2)
np.save('Regression_Daten/y_My_test2', y_My_test2)

np.save('Regression_Daten/y_Mz_train2', y_Mz_train2)
np.save('Regression_Daten/y_Mz_val2', y_Mz_val2)
np.save('Regression_Daten/y_Mz_test2', y_Mz_test2)"""

```

Out [56]:

```

"np.save('Regression_Daten/x_train', x_train)\nnp.save('Regression_Daten/x_val',
x_val)\nnp.save('Regression_Daten/x_test', x_test)\n\nnp.save('Regression_Daten/y_Fz_train1',
y_Fz_train1)\nnp.save('Regression_Daten/y_Fz_val1',
y_Fz_val1)\nnp.save('Regression_Daten/y_Fz_test1',
y_Fz_test1)\n\nnp.save('Regression_Daten/y_My_train1',
y_My_train1)\nnp.save('Regression_Daten/y_My_val1',
y_My_val1)\nnp.save('Regression_Daten/y_My_test1',
y_My_test1)\n\nnp.save('Regression_Daten/y_Mz_train1',
y_Mz_train1)\nnp.save('Regression_Daten/y_Mz_val1',
y_Mz_val1)\nnp.save('Regression_Daten/y_Mz_test1',
y_Mz_test1)\n\nnp.save('Regression_Daten/y_Fz_train2',
y_Fz_train2)\nnp.save('Regression_Daten/y_Fz_val2',
y_Fz_val2)\nnp.save('Regression_Daten/y_Fz_test2',
y_Fz_test2)\n\nnp.save('Regression_Daten/y_My_train2',
y_My_train2)\nnp.save('Regression_Daten/y_My_val2',
y_My_val2)\nnp.save('Regression_Daten/y_My_test2',
y_My_test2)\n\nnp.save('Regression_Daten/y_Mz_train2',
y_Mz_train2)\nnp.save('Regression_Daten/y_Mz_val2',
y_Mz_val2)\nnp.save('Regression_Daten/y_Mz_test2',
y_Mz_test2)"
```

In [57]:

```

plt.figure(num=None, figsize=(11, 5), dpi=300, facecolor='w', edgecolor='k'),
# plt.yticks([0,1,2,3])

plt.plot(np.linspace(1,len(y_Fz_train2)*0.05-0.05,len(y_Fz_train2)), y_Fz_train2, label='y_Fz_train2')

```

```

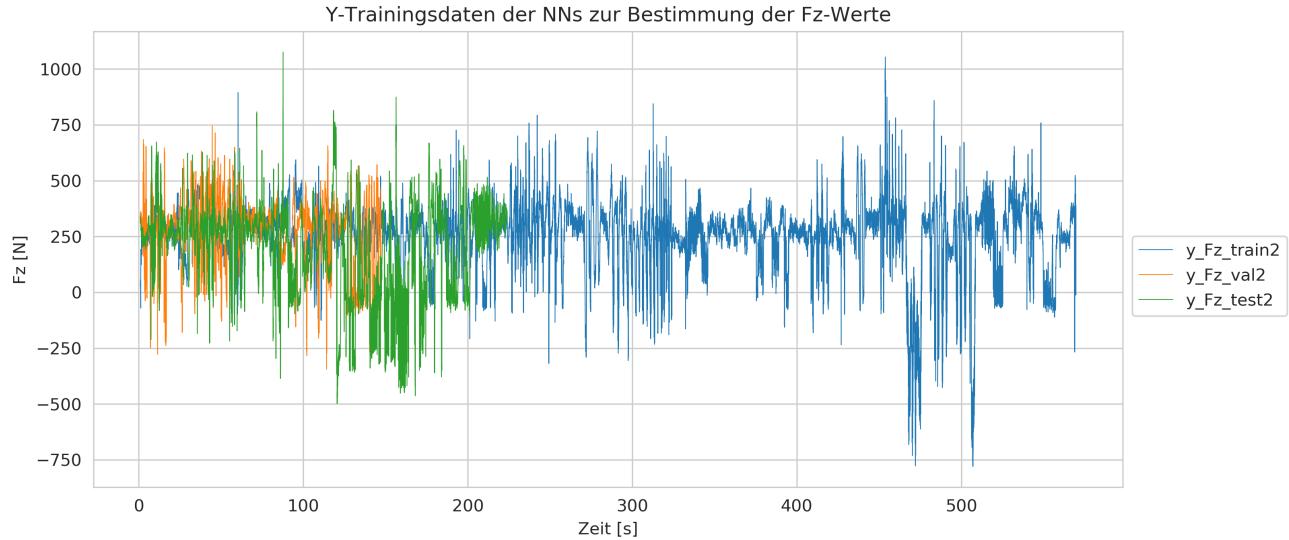
plt.plot(np.linspace(1,len(y_Fz_val2)*0.05-0.05,len(y_Fz_val2)), y_Fz_val2, label='y_Fz_val2',linewi
plt.plot(np.linspace(1,len(y_Fz_test2)*0.05-0.05,len(y_Fz_test2)), y_Fz_test2, label='y_Fz_test2',li

plt.title('Y-Trainingsdaten der NNs zur Bestimmung der Fz-Werte')
plt.xlabel('Zeit [s]')
plt.ylabel('Fz [N]')

plt.legend(bbox_to_anchor=(0.64, 0.15, 0.52, 0.4), borderaxespad=0)
#plt.xlim(left=600, right=800)

plt.show()

```



In [58]:

```

plt.figure(num=None, figsize=(11, 5), dpi=200, facecolor='w', edgecolor='k'),

# plt.yticks([0,1,2,3])

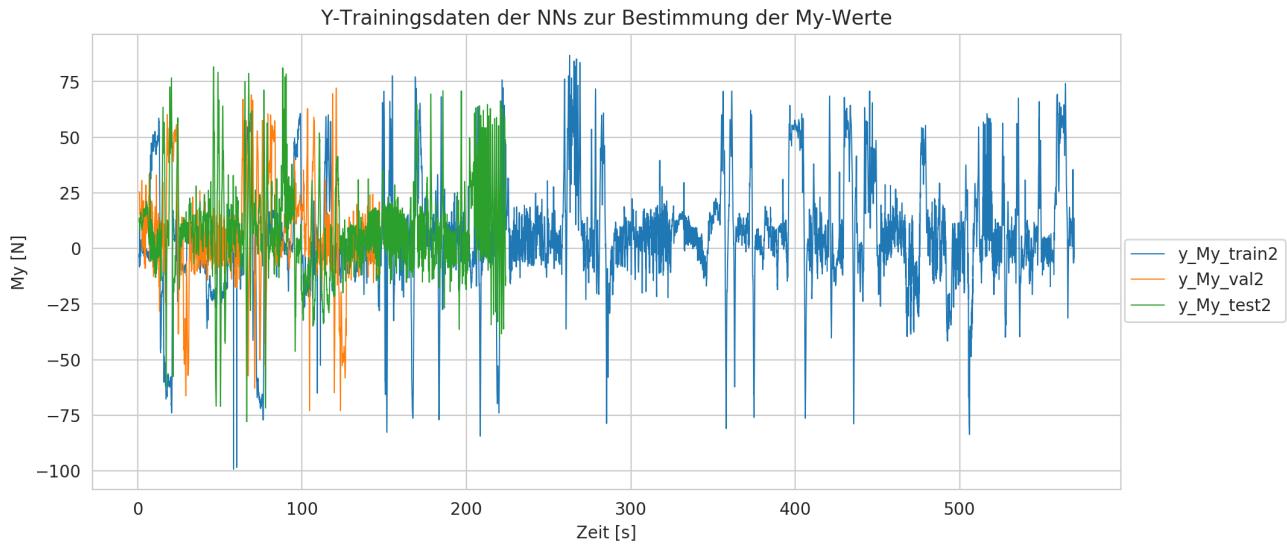
plt.plot(np.linspace(1,len(y_My_train2)*0.05-0.05,len(y_My_train2)), y_My_train2, label='y_My_train2')
plt.plot(np.linspace(1,len(y_My_val2)*0.05-0.05,len(y_My_val2)), y_My_val2, label='y_My_val2',linewi
plt.plot(np.linspace(1,len(y_My_test2)*0.05-0.05,len(y_My_test2)), y_My_test2, label='y_My_test2',li

plt.title('Y-Trainingsdaten der NNs zur Bestimmung der My-Werte')
plt.xlabel('Zeit [s]')
plt.ylabel('My [N]')

plt.legend(bbox_to_anchor=(0.64, 0.15, 0.52, 0.4), borderaxespad=0)
#plt.xlim(left=600, right=800)

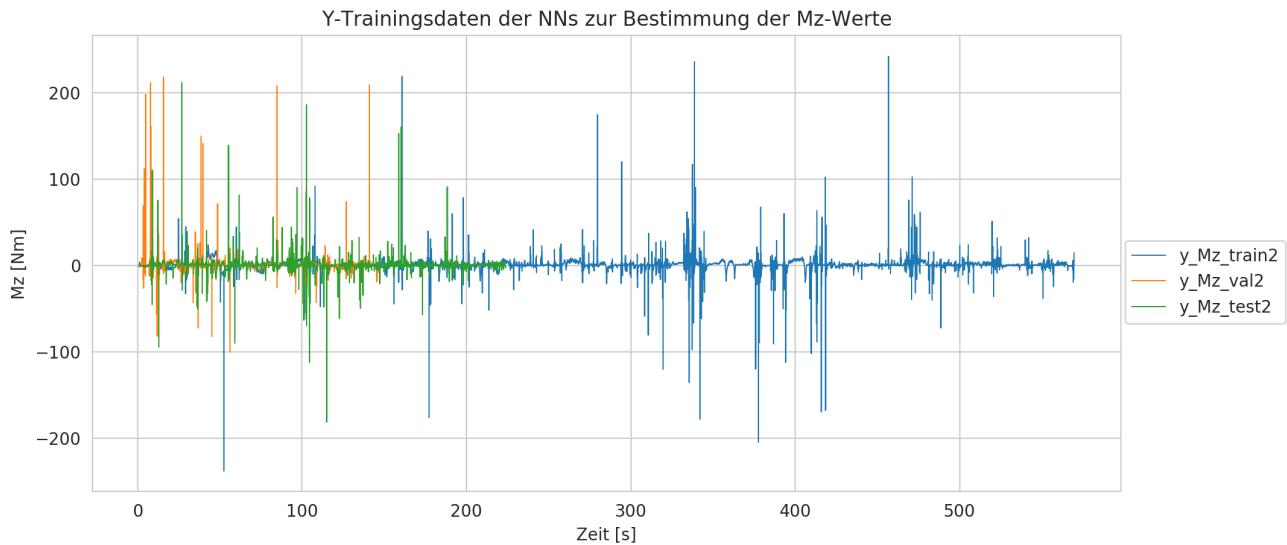
plt.show()

```



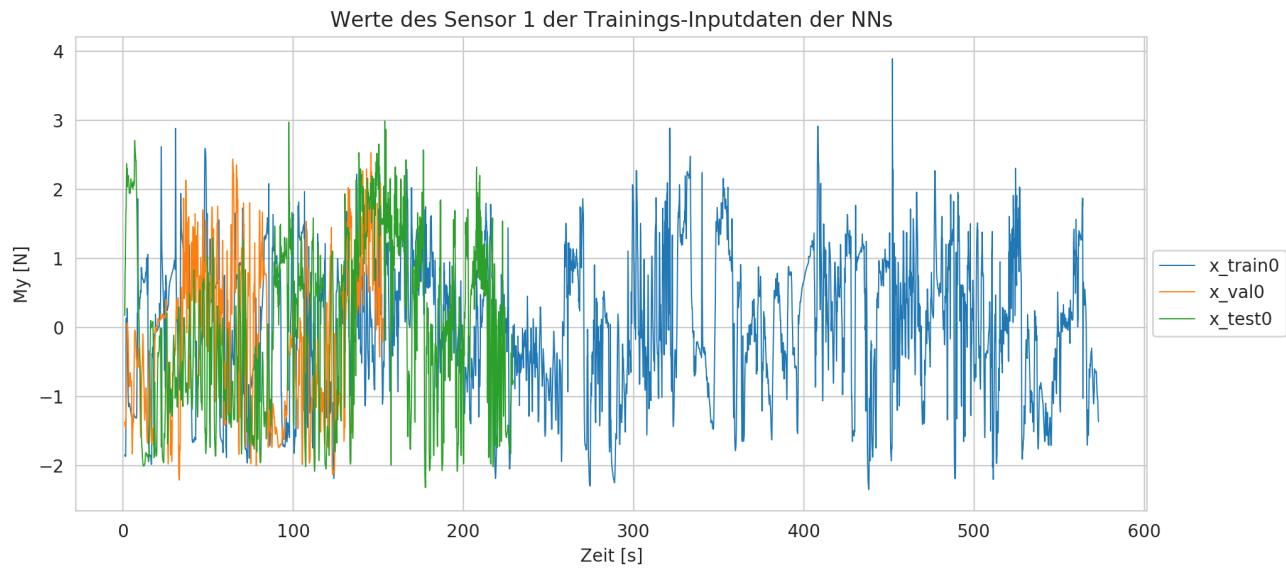
In [59]:

```
plt.figure(num=None, figsize=(11, 5), dpi=200, facecolor='w', edgecolor='k'),  
  
#plt.yticks([0,1,2,3])  
plt.plot(np.linspace(1,len(y_Mz_train2)*0.05-0.05,len(y_Mz_train2)), y_Mz_train2, label='y_Mz_train2')  
plt.plot(np.linspace(1,len(y_Mz_val2)*0.05-0.05,len(y_Mz_val2)), y_Mz_val2, label='y_Mz_val2', linewidth=2)  
plt.plot(np.linspace(1,len(y_Mz_test2)*0.05-0.05,len(y_Mz_test2)), y_Mz_test2, label='y_Mz_test2', linewidth=2)  
  
plt.title('Y-Trainingsdaten der NNs zur Bestimmung der Mz-Werte')  
plt.xlabel('Zeit [s]')  
plt.ylabel('Mz [Nm]')  
  
plt.legend(bbox_to_anchor=(0.64, 0.15, 0.52, 0.4), borderaxespad=0)  
#plt.xlim(left=0, right=100)  
#plt.ylim(bottom=-50, top=50)  
  
plt.show()
```



In [60]:

```
plt.figure(num=None, figsize=(11, 5), dpi=200, facecolor='w', edgecolor='k'),  
  
#plt.yticks([0,1,2,3])  
plt.plot(np.linspace(1,len(x_train0)*0.05-0.05,len(x_train0)), x_train0.MOA0, label='x_train0', linewidth=0.7)  
plt.plot(np.linspace(1,len(x_val0)*0.05-0.05,len(x_val0)), x_val0.MOA0, label='x_val0', linewidth=0.7)  
plt.plot(np.linspace(1,len(x_test0)*0.05-0.05,len(x_test0)), x_test0.MOA0, label='x_test0', linewidth=0.7)  
  
plt.title('Werte des Sensor 1 der Trainings-Inputdaten der NNs')  
plt.xlabel('Zeit [s]')  
plt.ylabel('My [N]')  
  
plt.legend(bbox_to_anchor=(0.61, 0.15, 0.52, 0.4), borderaxespad=0)  
#plt.xlim(left=0, right=100)  
#plt.ylim(bottom=-50, top=50)  
  
plt.show()
```



60% 16% 24%

In [61]:

```
train_p = int(len(y_mat)*0.6)  
val_p = train_p+int(len(y_mat)*0.16)  
test_p = len(y_mat)
```

In [62]:

```
plt.figure(num=None, figsize=(11, 2.5), dpi=200, facecolor='w', edgecolor='k'),  
coulumn_plt = 0  
  
plt.plot(np.linspace(1,train_p*0.05-0.05,train_p) ,y_mat[:train_p,coulumn_plt], label='Trainingsdaten')
```

```

plt.plot(np.linspace((train_p+1)*0.05,val_p*0.05-0.05,(val_p-train_p)) ,y_mat[train_p:val_p,couolumn_plt]
plt.plot(np.linspace((val_p+1)*0.05,test_p*0.05-0.05,(test_p-val_p)) ,y_mat[val_p:test_p,couolumn_plt]

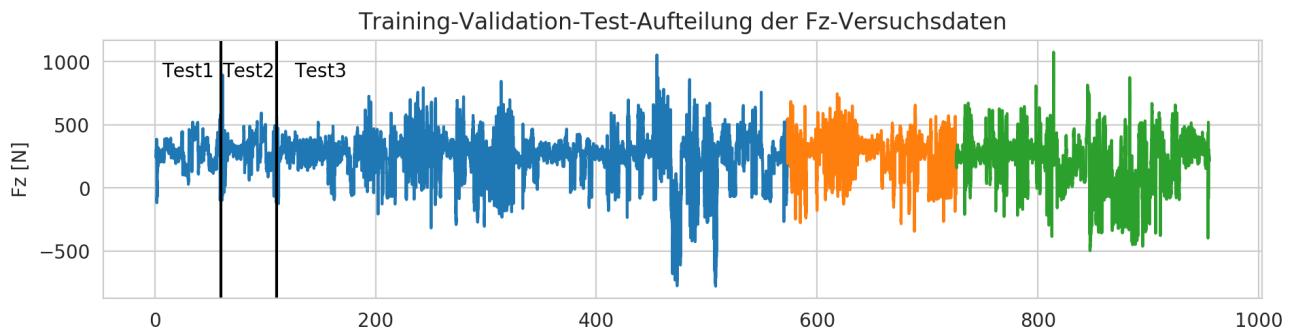
plt.title('Training-Validation-Test-Aufteilung der Fz-Versuchsdaten')
#plt.xlabel('Zeit [s]')
plt.ylabel('Fz [N]')
plt.axvline(x=len(y_mat1)*0.05, ymin=0, ymax=1, color='k')
plt.axvline(len(y_mat2)*0.05+len(y_mat1)*0.05, ymin=0, ymax=1, color='k')

#plt.legend(bbox_to_anchor=(0.72, 0.15, 0.5, 0.4), borderaxespad=0)
#plt.xlim(left=0, right=100)
#plt.ylim(bottom=-50, top=50)

plt.text(30, 1000, 'Test1',
         horizontalalignment='center',
         verticalalignment='top',
         multialignment='center', color='k')
plt.text(85, 1000, 'Test2',
         horizontalalignment='center',
         verticalalignment='top',
         multialignment='center', color='k')
plt.text(150, 1000, 'Test3',
         horizontalalignment='center',
         verticalalignment='top',
         multialignment='center', color='k')

plt.show()

```



In [63]:

```

plt.figure(num=None, figsize=(11, 2.5), dpi=200, facecolor='w', edgecolor='k'),
couolumn_plt = 1

plt.plot(np.linspace(1,train_p*0.05-0.05,train_p) ,y_mat[:train_p,couolumn_plt], label='Trainingsdaten')
plt.plot(np.linspace((train_p+1)*0.05,val_p*0.05-0.05,(val_p-train_p)) ,y_mat[train_p:val_p,couolumn_plt]
plt.plot(np.linspace((val_p+1)*0.05,test_p*0.05-0.05,(test_p-val_p)) ,y_mat[val_p:test_p,couolumn_plt]

plt.title('Training-Validation-Test-Aufteilung der My-Versuchsdaten')
plt.xlabel('Zeit [s]')
plt.ylabel('My [Nm]')

```

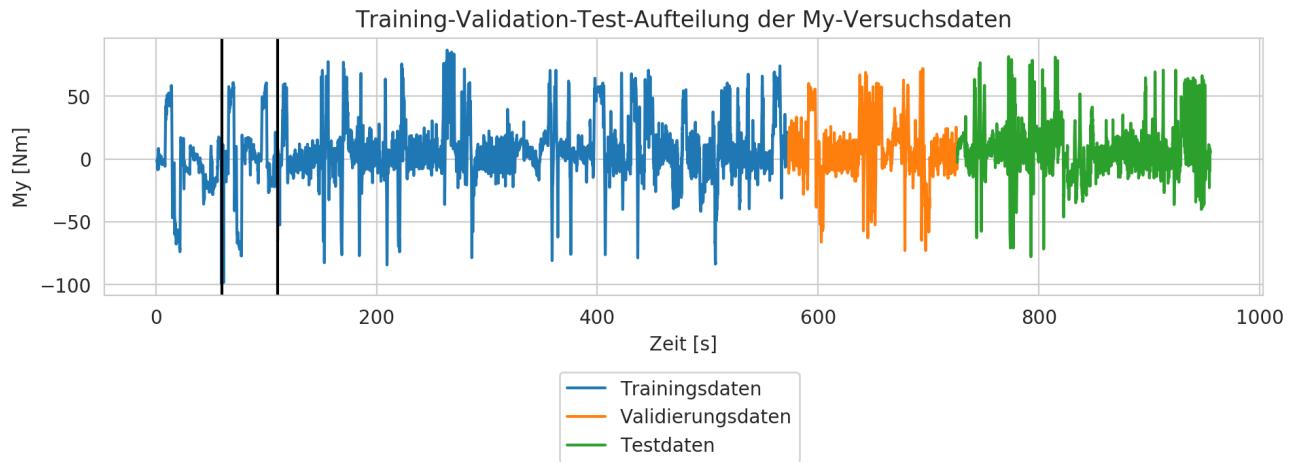
```

plt.axvline(x=len(y_mat1)*0.05, ymin=0, ymax=1, color='k')
plt.axvline(len(y_mat2)*0.05+len(y_mat1)*0.05, ymin=0, ymax=1, color='k')

plt.legend(bbox_to_anchor=(0.6, -0.3, 0., 0.), borderaxespad=0)
#plt.xlim(left=0, right=100)
#plt.ylim(bottom=-50, top=50)

plt.show()

```



In [64]:

```

plt.figure(num=None, figsize=(11, 2.5), dpi=200, facecolor='w', edgecolor='k'),
coulumn=plt = 2

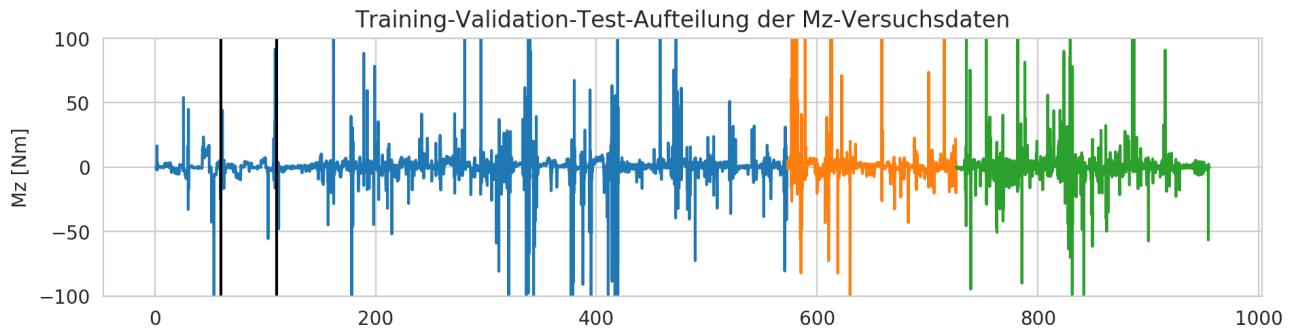
plt.plot(np.linspace(1,train_p*0.05-0.05,train_p) ,y_mat[:train_p,coulumn=plt], label='Trainingsdaten')
plt.plot(np.linspace((train_p+1)*0.05,val_p*0.05-0.05,(val_p-train_p)) ,y_mat[train_p:val_p,coulumn=plt], label='Validierungsdaten')
plt.plot(np.linspace((val_p+1)*0.05,test_p*0.05-0.05,(test_p-val_p)) ,y_mat[val_p:test_p,coulumn=plt], label='Testdaten')

plt.title('Training-Validation-Test-Aufteilung der Mz-Versuchsdaten')
#plt.xlabel('Zeit [s]')
plt.ylabel('Mz [Nm]')
plt.axvline(x=len(y_mat1)*0.05, ymin=0, ymax=1, color='k')
plt.axvline(len(y_mat2)*0.05+len(y_mat1)*0.05, ymin=0, ymax=1, color='k')

#plt.legend(bbox_to_anchor=(0.41, -0.3, 0., 0.), borderaxespad=0)
#plt.xlim(left=0, right=100)
plt.ylim(bottom=-100, top=100)

plt.show()

```



In [65]:

```
soctest1 = pd.read_csv('/Users/patrickcarqueville/Documents/Uni/Master/MA/SA/DataLogger/SockenVersuc
```

In [66]:

```
sns.set_palette('colorblind')
plt.figure(num=None, figsize=(11, 5), dpi=400, facecolor='w', edgecolor='k'),

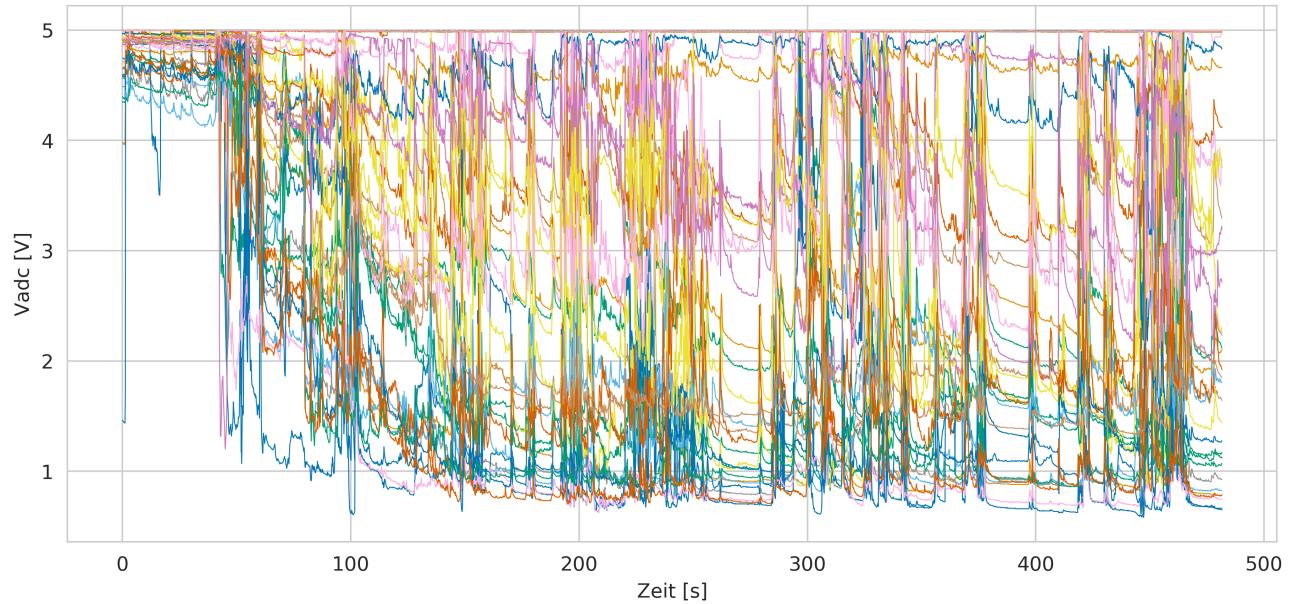
# plt.plot(np.linspace(1,train_p*0.05-0.05,train_p) ,y_mat[:train_p,couolumn_plt], label='Trainingsdaten')
# plt.plot(np.linspace((train_p+1)*0.05,val_p*0.05-0.05,(val_p-train_p)) ,y_mat[train_p:val_p,couolumn_plt])
# plt.plot(np.linspace(val_p+1)*0.05,test_p*0.05-0.05,(test_p-val_p)) ,y_mat[val_p:test_p,couolumn_plt]
plt.plot(np.linspace(0,3542*0.136-0.136,3542), soctest1.iloc[:,10:57]*5/1023,linewidth=0.5)

plt.title('Training-Validation-Test-Aufteilung der Mz-Versuchsdaten')
plt.xlabel('Zeit [s]')
plt.ylabel('Vadc [V]')
# plt.axvline(x=len(y_mat1)*0.05, ymin=0, ymax=1, color='k')
# plt.axvline(len(y_mat2)*0.05+len(y_mat1)*0.05, ymin=0, ymax=1, color='k')

# plt.legend(bbox_to_anchor=(0.41, -0.3, 0., 0.), borderaxespad=0)
# plt.xlim(left=0, right=100)
# plt.ylim(bottom=-100, top=100)

plt.show()
```

Training-Validation-Test-Aufteilung der Mz-Versuchsdaten



In [67]:

```
#socetest1
```